Neighborhood effects, public housing and unemployment in France

Florence Goffette-Nagot, Claire Dujardin

Neighborhood effects, public housing and unemployment in France*

Claire Dujardin
Université catholique de Louvain - FNRS †

Florence Goffette-Nagot
GATE - CNRS ‡

March 2007

*We would like to thank participants at the 2006 SOLE meetings, 2006 EALE conference, 2006 European RSA congress and 23° Journées de Microéconomie appliquée as well as Christian Belzil, Andrew Clark, Bernard Fortin, Laurent Gobillon, Claude Montmarquette and Henry Overman for useful comments and suggestions. Claire Dujardin thanks the FNRS for financing a research stay at GATE. Florence Goffette-Nagot acknowledges funding from the CNRS APN-program that allowed initiating this work. Data from the French National Institute for Statistics (INSEE) were provided by the LASMAS.

†Département de Géographie, Université catholique de Louvain, Place Pasteur 3, 1348 Louvain-la-Neuve, Belgium e-mail: dujardin@geog.ucl.ac.be.

‡GATE, CNRS - Université de Lyon 2 - ENS-LSH, 93 Chemin des Mouilles, 69131 Ecully, Tél: 33 +4.72.86.60.78. Fax: 33 +4.72.86.60.90. France email: goffette-nagot@gate.cnrs.fr. Corresponding author.

Neighborhood effects, public housing and unemployment in France

Abstract

This paper is aimed at estimating the effects of living in a deprived neighborhood on unemployment. Our identification strategy takes advantage of the situation of the public housing sector in France, which allows us to consider public housing accommodation as a shifter of neighborhood choice and to use household's demographic characteristics as exclusion restrictions. Using Census data for Lyon (France), we estimate a simultaneous probit model of unemployment, neighborhood type and public housing occupancy. Public housing accommodation does not have any direct effect on unemployment, but living within the 35% more deprived neighborhoods of Lyon significantly increases unemployment probability.

Keywords: Neighborhood effects, public housing, unemployment, simultaneous probit models, simulated maximum likelihood.
JEL code: R2, J64.

1 Introduction

A rapidly growing stream of research in the social interactions literature focuses on neighborhood effects, that is, the impact of neighbors' characteristics and behaviors on individual socio-economic outcomes.[1] In particular, theoretical and empirical evidence suggests that interactions among neighbors are likely to affect individual labor-market outcomes through peer effects and role models in the human capital acquisition process, attitudes toward work, and dissemination of information on job opportunities. Arnott and Rowse (1987) show that less-able learners exert negative externalities on the learning process of other students. Bénabou (1993) argues that the cost of education acquisition may be influenced by education decisions of neighbors. Wilson (1987) explains that the lack of successful role models among older adults in deprived neighborhoods may influence youths' motivations and attitudes toward work. The role of social networks on information about job openings has also been highlighted, especially for low-skilled workers who often resort to informal search modes such as personal contacts. As a consequence, the percentage of employed individuals in the neighborhood may influence other residents' access to job opportunities (Topa, 2001; Bayer et al., 2005). Finally, the stigmatization of deprived neighborhoods may lead employers to discriminate workers on the basis of their residential location (Zenou and Boccard, 2000).

Measuring neighborhood effects raises the issue of location choice endogeneity, which generates correlated effects (Moffitt, 2001; Durlauf, 2004). Indeed, urban economics has recognized for long that individuals with similar socio-economic characteristics, labor-market outcomes, and unobservable traits tend to sort themselves into certain areas of the urban space. Therefore, studies that do not control for the endogeneity of neighborhood choice will yield biased results. The inadequate correction for this bias has been put forward to explain the great divergence of results obtained by empirical studies and is one of the major focuses of recent research on neighborhood effects.

This paper aims to test for the existence of neighborhood effects on unemployment on French data. Our focus is not on disentangling endogenous and contextual effects as defined by Manski (1993), but on dealing with neighborhood endogeneity when estimating its global effect on unemployment probability. We argue that the French situation provides an interesting opportunity to do so. Indeed, the large share of public housing units in France and their concentration in poor neighborhoods, where they may represent as much as two thirds of the

[1] See Durlauf and Young (2001) for a review of this literature and Durlauf (2004) for that on neighborhood effects.

housing stock, makes public housing accommodation a powerful determinant of location in these neighborhoods. Furthermore, due to a shortage in available public housing units, criteria used in the public housing assignment process in France do not only rely on the household's economic situation, but depend also strongly on its demographic characteristics such as age and composition. We use these demographic criteria as exclusions for identifying our empirical model. This model consists in classifying neighborhoods as deprived or not deprived in a preliminary data analysis step and estimating a simultaneous probit model of unemployment, type of neighborhood and public housing accommodation. The second and third probit equations of public housing accommodation and neighborhood type are meant at accounting for the endogeneity of tenure and location choice. This strategy, that involves considering both public housing tenants and other households, also allows us to test for potential damaging effects of public housing accommodation, which is known to reduce residential mobility and may thus affect job search. Estimations of this simultaneous probit model are performed on a sample of approximately 10,000 individuals, taken from the 1999 French Census and representing about five percents of household heads participating in the labor-market in Lyon, the third largest city in France.

The main contributions of this work are (i) the estimation of neighborhood effects on unemployment in a model dealing with endogeneity of location choice and (ii) the test for a negative influence of public housing accommodation on unemployment on European data. Our results show that living in a neighborhood displaying a combination of low-skilled population, high unemployment rate, and high proportion of foreigners increases the unemployment probability significantly. Our estimate is comparable to that Topa (2001) obtained for Chicago and complements more recent work such as Weinberg et al. (2004) and Bayer and Ross (2006) for the US. However it contradicts recent results obtained by Bolster et al. (2007) showing no neighborhood influences on income trajectories in Britain. We also find that public housing does not have any detrimental effect on unemployment, thus complementing Jacob's (2004) results concerning public housing and educational outcomes in the U.S and Flatau et al. (2003) estimates of the effect of tenure on unemployment in Australia. Still, an indirect effect of public housing accommodation on unemployment probability is shown to exist through the effect of tenancy on the probability to live in a neighborhood that generates negative spillovers on unemployment. Therefore, our results shed light on the potential effects of a recent French law aimed at achieving a more even spatial distribution of public housing units within cities. This finding might probably be extended to other countries having a large share of public housing units.

The paper is structured as follows. Section 2 presents our identification strategy, the empirical model and the econometric method. Section 3 describes the database and gives a brief description of the spatial structure of Lyon. Section 4 presents the main results and section 5 concludes.

2 Model specification

2.1 Identification strategy

In his widely cited article, Manski (1993) considers two effects by which the social group may impact an individual's behavior. Individual behavior can be influenced either by the average behavior or by characteristics of the members of his reference group. The first effect is referred to as an endogenous effect, while the latter is called a contextual effect. Moreover, similar behaviors in a group can be the consequence of exposure to common unobserved factors or of non random group selection. Those mechanisms generate what is referred to as correlated effects.

The goal of contemporaneous work on neighborhood effects is to disentangle these different kinds of mechanisms. Neighborhood effects consist in endogenous and contextual effects, each of which, if shown to exist, has different policy implications (Moffitt, 2001; Glaeser and Scheinkman, 2001). Correlated effects, if not corrected for, bias the estimates of neighborhood effects. Recent empirical studies highlight the reduction of estimated neighborhood effects that stems from correcting for such biases (Ginther et al., 2000; Krauth, 2005). The endogeneity of group membership in particular is likely to generate large biases, because individuals sort themselves into neighborhoods depending on their observable and unobservable characteristics.

The objective of this work is to estimate neighborhood effects on unemployment, focusing on the correction for selection into neighborhoods. We do not try to disentangle endogenous and contextual effects, but we aim at providing an estimate of their global effect on unemployment probability.

Various strategies have been developed to correct for neighborhood endogeneity in the study of neighborhood effects. Instrumental variables methods were often used, some of them relying on aggregate data for instrumentation, but Rivkin (2001) shows that using aggregate variables as instruments may actually increase the endogeneity bias. Quasi-experimental situations such as the Gautreaux Program and the Moving To Opportunity program provided more reliable estimates of neighborhood effects on labor-market outcomes (see Oreopoulos, 2003 for a review and Liebman et al. (2004) for recent evidence on MTO). However, we are not aware of any such possibility in the French case. A third strand of literature uses aggregate statistics and their variation in space to assess the importance of neighborhood effects (Glaeser et al., 1996; Topa, 2001).

The problem with instrumental variables methods is to have suitable instruments. We argue that the French situation gives the opportunity to do so. In a nutshell, our identification strategy takes advantage of two characteristics of the public housing sector in France. First, public housing units are concentrated in peripheral neighborhoods of French cities. As a consequence, public housing occupancy strongly affects location choices and renters in the public sector are far more likely than others to live in a deprived neighborhood. Second, applications for public housing accommodation largely exceed supply and public housing offices not only consider the household's economic situation for attribution, but also its demographic situation. This allows us to use demographic characteristics as exclusion restrictions to identify a three probits system in which we explain simultaneously public housing occupancy, location in a deprived neighborhood and unemployment. Furthermore, because our dataset is at the household level, we are also able to use the spouse's educational level as a supplementary instrument.

In a more detailed manner, more than a third of the public housing stock in France was built between 1962 and 1974, mostly under the form of large projects located at the periphery of urban cores, thus providing a powerful source of income segregation. As a consequence, public housing accommodation is a strong determinant, along with observable and unobservable household's characteristics, of location in a deprived neighborhood. Still, not every public housing unit is located in a deprived neighborhood and public housing tenants have some latitude in choosing their neighborhood. Indeed, households which are offered a public housing unit may accept or refuse the proposal, and in the latter case receive new proposals later. In 2002, one quarter of households housed in the public housing sector in France had rejected at least one offer before accepting one; half of these refusals were justified by the fact that *"the housing unit was in a neighborhood that did not fit household's preferences"* (Insee[2], 2002 French Housing Survey). Of course, those having the most urgent need of an affordable housing are the most likely to accept the first proposal. Therefore, location of public housing renters is likely to be influenced by individual's prospects on the labor market. Selective moves out of public housing in unattractive locations probably reinforce such effects. In other words, despite the administrative procedure of assignment of public housing units to households, a sorting of public housing renters into neighborhoods, based on observable and unobservable characteristics, can not be excluded *a priori*. Hence, location would potentially be endogenous if we were to estimate the effect of location on unemployment based on the population of public housing renters only, as

[2] French National Institute for Statistics.

was done by Oreopoulos (2003) in Canada to estimate neighborhood effects on schooling.[3] As a result, we estimate the effect of location on unemployment on the whole population, using public housing occupancy as a shifter of household's location. In doing so, we have to account for the potential endogeneity of public housing occupancy. Indeed, the same mechanisms that lead to an endogenous selection of public housing renters into neighborhoods are likely to result in a selection of households into the public housing sector.

The French housing policy is characterized by the fact that, although the public housing sector accounts for 17% of the French housing stock, eligible households (those meeting an income ceiling criteria) represent as much as two thirds of the population.[4] Therefore, demand for public housing accommodation largely exceeds available housing units and applications are ranked by local public housing offices on waiting lists, subject to several criteria pertaining in particular to the demographic situation. For instance, public housing offices give priority to single-parent families and couples with young children. Therefore, we are able to use the number of children and the presence of young children in the household as exclusion restrictions in our empirical model. As will be clear from our results, both of them influence tenancy and they are not likely to affect location nor employment status. These exclusions are complemented by the spouse's educational level. We provide several checks supporting these identifying assumptions in the following.

Our goal being to estimate neighborhood effects, we have of course to define a relevant measure of neighborhood characteristics. Literature on neighborhood effects shows that a wide variety of neighbors' characteristics is likely to affect individual unemployment propensity.[5] Introducing all of them is not desirable because of the high degree of correlation observed between such variables, which may cause instability in the parameters and significance levels (O'Regan and Quigley, 1998). Furthermore, potential threshold effects in the influence of neighborhood do not make desirable to estimate a linear model (Crane, 1991, Weinberg et al., 2004). Consequently, we account for the influence of neighborhood through a dummy variable indicating whether each neighborhood of Lyon may be considered, on the basis of the social characteristics

[3] Goux and Maurin (2007) also consider the location of public housing renters as exogenous in the French case. As shown below, our results do not contradict this view, although we prefer not to consider it as valid *a priori*.

[4] As a result, according to the 2002 French Housing Survey, 20% of public housing renters belong to the four highest deciles of the income distribution (Jacquot, 2007).

[5] Neighborhood could also affect individual outcomes through distance to job opportunities, as argued in the spatial mismatch literature (Gobillon et al., 2007). However, preliminary tests on our sample of the impact of time distance on unemployment probability did not reveal any empirical support for the spatial mismatch hypothesis, which was therefore left aside.

of its residents, as likely to generate negative spillovers in terms of unemployment. As will be detailed in section 3.2, the neighborhood type is defined through a data analysis step based on population characteristics likely to influence information on job opportunities, role models, peer effects in human capital acquisition or to generate statistical discrimination.

Including neighborhood type in variables affecting unemployment allows us to test for the presence of neighborhood effects. In order to correct for the potential endogeneity of neighborhood type, we have to simultaneously estimate a probit for unemployment and a probit for location in a deprived neighborhood. The neighborhood equation has to include public housing accommodation among covariates. We therefore add a third probit model for public housing occupancy to account also for the potential endogeneity of public housing accommodation in the neighborhood equation. Estimating simultaneously the three probits is a simple way to deal with the endogeneity issue (Greene, 1998). As we explained above, we use exclusion restrictions, although the identification of a simultaneous probit model does not formally require them (Wilde, 2000). Furthermore, the simultaneous probit accounts for correlation between unobservables by explicitly estimating the correlation matrix of residuals.

This strategy permits us to test also for potential detrimental effects of public housing accommodation on unemployment. Indeed, residing in a public housing unit may affect labor-market opportunities of individuals not only by constraining their residential location choices but also by reducing their subsequent residential mobility. In France, public housing renters are at risk of not obtaining another public housing unit if they move home.[6] Consequently, they bear higher mobility costs, that may raise their reservation wage and increase their unemployment probability. In order to test for such an effect, the public housing variable is also included in the unemployment probit equation. The next section presents the resulting empirical model.

2.2 Empirical model and econometric method

Our empirical model is intended to test for the effect of neighborhood deprivation and public housing accommodation on unemployment. We only deal with couple households, because the case of single adults suffers from a selection bias, young adults being less likely to form a separate household if they are unemployed. Moreover, because dealing with women would imply to explain not only unemployment, but also labor-market participation, our study only concerns the household head.

[6] As a matter of fact, annual mobility rates of public renters are at 10 percent against 16 percent in the private sector (Debrand and Taffin, 2005).

Although the classical theory of job search ends up in the estimation of unemployment duration models, our dataset only allows us to estimate the probability of unemployment. This reduced form is assumed to represent both how neighborhood characteristics affect the arrival rate of job offers and how they impact reservation wages. Unemployment is then explained, in a classical manner, by individual characteristics relative to experience (that will be proxied by age and its square to allow for a non-linear effect), education and previous occupation, because unemployment rates vary with skill level and professional status. The individual's nationality is included in order to account for potential discrimination by employers. The spouse's nationality is used as a proxy for the access to information on job opportunities through the network of relatives, as opposed to the social network provided by the neighborhood. Lastly, the two residential variables of neighborhood type and public housing accommodation are included as explanatory variables of unemployment in order to test our hypotheses.

As already explained, tenancy in the public housing sector strongly influences the type of neighborhood where a household lives. Public housing accommodation is therefore introduced among covariates in the neighborhood equation. Further, due to their unattractiveness, market housing prices in deprived neighborhoods are lower than in other neighborhoods (See Figure 3 in the next section). Therefore, household income influences the probability to live in a deprived neighborhood. It will be proxied by occupational status in previous job, educational level of the individual and his spouse, and age. Because educational level of the spouse is not likely to influence the individual's unemployment probability, it is used as an exclusion restriction. Finally, neighborhood type might also be explained by household size, that determines housing floor space need and thus the propensity to settle in neighborhoods where housing prices are low. Still, first tests showed no effect of the number of children on neighborhood type, once it is accounted for the effect of tenancy. This probably results from the preferential attribution of public housing units to large families: large families in search of affordable housing do not have to rent in the private sector, which rules out any direct effect of family size on neighborhood type.

Accommodation in the public housing sector (which reflects both that the individual applied for, obtained and is still in a public housing unit at the observation date) is determined in the first place by household income, that will be proxied by the same variables as in the neighborhood equation. Further, as we already explained, variables relative to household composition and age of its members are taken into account by public housing offices and are likely to explain tenancy. In particular, young households and large families are given preferential attribution of public housing units. The demographic characteristics showing the strongest influence on public housing accommodation revealed to be the presence of children of 6 or below, and of four children or more. The former might particularly explain the propensity to enter the public housing sector and the latter is likely to decrease the propensity to leave it. Indeed, large families encounter difficulties in finding affordable housing, unless they have a high income. These two variables are included in the public housing equation and as they do not show any influence on unemployment nor on neighborhood type, they are excluded from the corresponding equations.

As our simultaneous probit model includes two endogenous observed discrete variables on its right hand side (neighborhood type and public housing in the unemployment equation and public housing in the neighborhood choice equation), it amounts to a mixed model. This kind of simultaneous model requires a coherency condition, which imposes a triangular form (Maddala, 1983; Blundell and Smith, 1994). That is, the observed variable of unemployment can not be introduced in the other two equations, nor the neighborhood type in the public housing equation. Of course, unemployment is likely to affect entry in the public housing sector and to prevent households from leaving it. By decreasing the household's income, it also affects the propensity to live in a deprived neighborhood. To account for these influences while satisfying the coherency condition, we are restricted to include all the exogenous variables influencing unemployment in the other two equations. In doing so, we take into account the effect of observable characteristics determining unemployment probability on the residential situation. A potential problem comes from the fact that unobservables influencing unemployment are not accounted for, in particular in the public housing equation. This would be likely to ensue in the correlation of the error terms of the public housing equation and the unemployment equation. The simultaneous probit model ensures that this correlation is explicitly dealt with, as the correlation matrix of error terms is estimated. Similarly, all the variables determining the latent variable of neighborhood type are included in the public housing equation to account for potential effect of neighborhood choice on the propensity to apply for a public housing unit. As a result, this simultaneous probit model is to be considered as a model in which there is one equation of interest (the unemployment equation) and the other two equations are nothing but reduced forms. From this viewpoint, what is important in order for the effects of neighborhood type and tenure in the unemployment equation to be identified, is to have relevant exclusion restrictions.

In summary, the observed variables y_1, y_2 and y_3 referring respectively to unemployment, location in a disadvantaged neighborhood and public housing accommodation are defined by:

$$y_1 = \begin{cases} 1 & \text{if } y_1^* > 0, \\ 0 & \text{otherwise} \end{cases} \tag{2.1}$$

$$y_2 = \begin{cases} 1 & \text{if } y_2^* > 0, \\ 0 & \text{otherwise} \end{cases} \tag{2.2}$$

$$y_3 = \begin{cases} 1 & \text{if } y_3^* > 0, \\ 0 & \text{otherwise} \end{cases} \tag{2.3}$$

where y_1^*, y_2^* and y_3^* are latent variables influencing the probability of unemployment, the probability to live in a deprived area, and the probability to be renter in the public sector respectively.

The system of latent variables is as follows:

$$\begin{cases} y_1^* &= \alpha_1 X_1 + \beta y_2 + \gamma y_3 + u_1 \\ y_2^* &= \alpha_2 X_2 + \delta y_3 + u_2 \\ y_3^* &= \alpha_3 X_3 + u_3 \end{cases} \tag{2.4}$$

where X_1 is a vector of exogenous variables including a constant, individual's age and its square, nationality, diploma and previous occupation as well as the spouse's nationality (each of them being a set of dummy variables), X_2 includes the same set of variables as X_1 and dummies for the spouse's diploma and X_3 includes the same set of variables as X_2 and dummies for the presence of children below 6 and for having four children or more. β and γ test for the influence on unemployment probability of neighborhood type and public housing accommodation respectively. The exclusion of the dummies for the presence of children below 6 and for having four children or more in the neighborhood equation, and of the former two and spouse's education level in the unemployment equation ensures that this system is identified. The complete list of variables and their descriptive statistics for employed and unemployed individuals are given in Table 1.

As we assume that the sorting of households into deprived neighborhoods may be affected by unobserved characteristics influencing simultaneously unemployment and residential choice, the correlation terms between the residuals of the three probits (u_1, u_2 and u_3) are all supposed to be non-zero. The vector of residuals (u_1, u_2, u_3) follows thus a normal trivariate law with zero means and a covariance matrix that writes, after normalizations to 1 of the diagonal elements as usual in probit models:

$$Cov(u_1, u_2, u_3) = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{12} & 1 & \rho_{23} \\ \rho_{13} & \rho_{23} & 1 \end{bmatrix} \tag{2.5}$$

Such a system can be estimated by a maximum likelihood method. Endogeneity tests amount to test the significance of the correlation coefficients of residuals for each pair of equations.

Further, although our identification strategy allows us to deal with the endogeneity of neighborhood choice, estimated neighborhood effects could still be suspected to suffer from other biases due to random shocks common to all individuals in deprived neighborhoods, that are known to generate correlated effects. Our sample having a large number of neighborhoods and few individuals in each of them (with on average 20 sampled individuals per neighborhood), coefficients of neighborhood-level variables (which is the case of neighborhood type) are consistently estimated, but the variance matrix must be corrected for within-neighborhoods dependence (Wooldridge, 2003). This is the reason why we use Huber adjusted standard errors which accounts for the potential dependence of residuals within neighborhoods.

Individual contributions to the likelihood can be written as follows:

$$\begin{aligned} &P(y_{i1}, y_{i2}, y_{i3}) = \\ &\quad \Phi_3[q_{i1}(\alpha_1 X_{i1} + \beta y_{i2} + \gamma y_{i3}) \ , \ q_{i2}(\alpha_2 X_{2i} + \delta y_{i3}) \ , \ q_{i3}(\alpha_3 X_{3i}) \ , \\ &\qquad q_{i1}q_{i2}\rho_{12} \ , \ q_{i1}q_{i3}\rho_{13} \ , \ q_{i2}q_{i3}\rho_{23}] \end{aligned} \tag{2.6}$$

where $q_{ij} = 2y_{ij} - 1$ is equal to 1 whenever y_{ij} is 1 and to -1 whenever y_{ij} is 0, subscript i denotes individual i and $\Phi_3(.)$ is the trivariate normal cumulative distribution function. The log-likelihood function is then:

$$lnL = \sum_{i}^{N} lnP(y_{i1}, y_{i2}, y_{i3}) \tag{2.7}$$

The calculation of individual contributions requires to integrate over the distribution of the vector of three error terms, which means the complex calculation of a triple integral. Simulated maximum likelihood methods have been developed to circumvent this problem. One of the simulators commonly used is the GHK (for Geweke-Hajivassiliou-Keane) simulator.[7] The accuracy of the GHK simulator is good as soon as the number of random draws is equal to or higher than the square root of the sample size (Cappelari and Jenkins, 2003). With a sample of 10,473 individuals, we use 600 replications for each estimation, which is far above this threshold.

[7]The principle of this simulator is to use the lower triangular Cholesky decomposition of the covariance matrix of error terms to replace correlated random variables by uncorrelated ones, which are drawn from truncated normal density functions. Individual contributions to the likelihood are calculated as averages over several repeats of the random draw. See for example Bolduc (1999) for a presentation of the GHK simulator and its use in a multinomial probit model.

3 Data and basic evidence

3.1 Data

This paper focuses on Lyon, the third largest city in France. Its agglomeration (defined here by its urban unit[8]) extends over a 958 km^2 area and hosts around 1.3 million inhabitants. As shown in the next subsection, Lyon, like many other French and European cities, is characterized by the existence of pockets of unemployment in the close periphery of its center and thus appears to be an adequate case study to test for the existence of neighborhood effects.

The empirical analysis conducted in this paper is based on two datasets extracted from the 1999 French Population Census. Although they present some disadvantages (e.g. lack of data on housing price and household income, as well as on unemployment duration), Census data are interesting to use in such a context as it is the only source of data that provides a sample size sufficiently large as to provide accurate estimates of neighborhood effects for a given city. Moreover, the French Census allows to identify the location of individuals in very small geographical areas, called *Iris*, which are the finest geographical level available (for the sake of simplicity, they will be called neighborhoods in the rest of the paper). These neighborhoods are either municipalities, or subdivisions of municipalities if the latter have more than 10,000 inhabitants. Our study area has 543 neighborhoods.[9] They have on average 2,425 inhabitants, a figure more or less comparable to the size of American Census tracts used in previous studies of neighborhood effects in the U.S. (Table A.2 in appendix). Only 46 of them have more than 3,500 inhabitants. These spatial subdivisions have been delineated in order to represent homogeneous entities in terms of housing and population. They are generally formed around well identified groups of buildings and respect frontiers such as main avenues, rivers or railways. Thus, they can be considered as meaningful from the viewpoint of residents' day-to-day life.

Our first dataset includes the whole population of Lyon and gathers summary statistics at the neighborhood level for various indicators of the socioeconomic composition and average housing characteristics. This data is used to define the typology of neighborhoods (see next subsection). The second dataset corresponds to a sample of individuals (1/20th of the total

[8]The urban unit, *unité urbaine* in French, is a set of municipalities, the territory of which is covered by a built-up area of more than 2,000 inhabitants, and in which buildings are separated by no more than 200 meters. The urban unit of Lyon consists of 102 municipalities. For practical reasons, we added three municipalities which are enclosed within the urban unit of Lyon (Quincieux, Saint-Germain-au-Mont-D'Or and Poleymieux-au-Mont-D'Or).

[9]A few *Iris* having less than 200 people had to be deleted for confidentiality reasons.

population), for whom detailed personal, household, and housing characteristics are provided (age, gender, education[10], employment status, household type, housing tenure, ...) along with the characteristics of the other members of his household. This dataset allows to link each individual to the neighborhood in which he lives in. It is used to estimate our empirical model. As we already explained, our study deals with heads of couple households, aged 19 to 64 and participating in the labor-market. Due to data availability on previous occupation, we deleted individuals who never worked, that is only 18 individuals. The final sample contains 10,473 individuals, all of them being males.

3.2 Neighborhood typology

The agglomeration of Lyon presents a well-marked spatial structure, with some parts of the city characterized by a concentration of disadvantaged communities. Figure 1 maps the percentage of unemployed workers among labor-force participants. In most American cities, peripheral neighborhoods exhibit lower unemployment rates than central neighborhoods. In Lyon also, the neighborhoods with the lowest unemployment rates are found in the periphery, but Figure 1 shows that the highest unemployment rates are not found in the center, but in the Eastern part of an intermediate ring.

This pattern is very typical of French cities and is explained by the location of public housing units, a large fraction of which was built under the form of large projects at the city periphery in the 1970's. Since then, the city expanded further away under the form of wealthier suburbs. These public housing projects now play a strong role in the spatial concentration of low-income households. Indeed, in Lyon's agglomeration, the Duncan index measuring the segregation of public housing units compared to other housing units is 52.7, which means that more than half of the existing housing stock would have to be displaced in order to achieve an even spatial distribution of the two types of housing.[11] In some of the neighborhoods displaying the highest unemployment rates, more than 50% of households (and even more than 70% for

[10]In the whole paper, the following education levels will be used: No diploma, At most lower secondary school, Vocational training, High school final diploma, University degree. They correspond to the following French categories: no reported diploma, CEP or Brevet, CAP or BEP, *Baccalauréat*, DEUG or above, respectively.

[11]The Duncan index, or dissimilarity index, is commonly used in segregation studies and is defined as

$$D = \frac{1}{2} \sum_i \left| \frac{PH_i}{PH} - \frac{nonPH_i}{nonPH} \right|$$

where PH_i is the number of public housing units in neighborhood i, PH is the number of public housing units in the whole city, $nonPH_i$ is the number of other housing units in neighborhood i and $nonPH$ is the number of other housing units in the whole city (Duncan and Duncan, 1955).

a few of them) are housed in the public renting sector (Figure 2). Those neighborhoods with high levels of unemployment and large shares of public housing have above average rates of low-educated, blue-collar workers and ethnic minorities. As a consequence, one can suspect the existence of neighborhood effects affecting labor-market outcomes of individuals located in these neighborhoods.

Finally, figure 3 maps average market housing prices at the municipality level (in French, *Communes*) for housing units in apartment buildings that were sold in 1999.[12] It witnesses the unattractiveness of those eastern and intermediate locations and conversely shows the potential role of housing prices in location choices of low-income households.

Our typology of neighborhoods is aimed at reflecting for each neighborhood its social composition and the neighborhood effects that might potentially affect labor-market outcomes. Therefore, it is based on a set of variables chosen in order to account for the three most-often cited groups of mechanisms by which neighborhood might affect unemployment. First, employment status might be influenced by the quality of social networks, as these are important determinants of the quantity and quality of available information on job opportunities, especially for low-skilled workers (see Holzer, 1988 for empirical evidence and Selod and Zenou, 2001 for a theoretical model). In our typology, the quality of social networks is represented through two variables: unemployment rate (which reflects the fact that in high-unemployment neighborhoods, individuals know few employed people that could inform them about job openings) and percentage of household heads of foreign nationality (because foreign communities are often isolated from the social networks that are useful in finding a formal job). The second mechanism highlights the importance of role models and peer effects (Wilson, 1987). These will be captured by a set of variables reflecting the distribution of population by educational levels, the percentages of executives and blue-collars in labor force (which serve as proxies for income levels), and the percentage of lone-parent families. All these variables are indicators of social and economic success (or unsuccess) among neighbors, which can generate imitative behaviors and contagion effects. Finally, the stigmatization of deprived neighborhoods may lead employers to discriminate workers on the basis of their residential location (a practice which is known as *redlining*, see the model of Zenou and Boccard, 2000). This effect is captured also by the percentage of household heads of foreign nationality and by the proportion of lone-parent families (which is often correlated to other social deviances giving rise to the stigmatization of neighborhoods). In summary, our typology of neighborhoods is based on the following variables: unemployment

[12]Municipalities for which the figure is available are the closest from the city center, because houses are more frequent on the periphery.

rate, long-term unemployment rate, percentage of families with foreign household head, distribution of population by education level and occupational status, and percentage of lone-parent households. This set of variables is quite similar to the one used by Bolster et al. (2007), who use in addition variables characterizing the housing stock.

Introducing all these characteristics as covariates in an unemployment equation is not desirable because they are highly inter-correlated, which may cause collinearity problems (O'Regan and Quigley, 1998). Therefore, we treat this set of variables by means of standard factorial ecology methods (see for example Johnston et al., 2004). We first ran a Principal Component Analysis to define non-correlated factors summarizing the information carried by these variables. Two factors with eigenvalues higher than one were retained, which account together for 90% of the variance of our initial set of variables (see Table A.1 in Appendix). Then, a composite indicator is built by linearly combining neighborhoods' coordinates on the two factorial axes.[13] This composite variable can be understood as an indicator of a neighborhood's degree of deprivation. Then, we ran a hierarchical ascending classification on the basis of the composite indicator (with the Ward criterion which minimizes intra-group variance) in order to define deprived neighborhoods versus not-deprived neighborhoods so as to end up with a dummy variable. However, the hierarchical ascending classification with only two groups was not sastifying, because it defines a small group of very deprived neighborhoods, in which the majority of housing units belong to the public sector, whereas our identification strategy supposes to have a mix of public housing and other tenures in deprived neighborhoods. Therefore, we defined the deprived neighborhoods on the basis of a four-groups classification[14] in which we grouped the two classes corresponding to the most deprived neighborhoods.

This means that we defined as deprived the 191 neighborhoods (i.e. 35 % of Lyon's neighborhoods) with the highest scores for the deprivation indicator, thus defining the endogenous variable y_2. These neighborhoods are spread in different parts of the city, still mostly concentrated in its eastern half (Figure 4). They are characterized by high unemployment rates (twice as high as the average unemployment rate of other neighborhoods), high percentages of foreign

[13]In this linear combination, each axis is weighted by the percentage of total variance explained, i.e. 0.7374 for factor 1 and 0.1673 for factor 2; see Table A.1 in Appendix.

[14]The classification with three groups was also unsatisfying, because it only separates "good" neighborhoods at the other end of the ranking based on the composite indicator. The four-groups classification is as follows: a group of very deprived neighborhoods (with 0.75 as cutt-off value) which concentrates essentially neighborhoods with very high percentages of public housing renters, a group of deprived neighborhoods (with 0.08 as cutt-off), a group of neighborhoods with average characteristics (with -0.35 as cutt-off) and a last group of more well-off neighborhoods.

nationalities and low educational levels and occupational statuses (Table A.2 in Appendix). Most of them have a large share of public housing, but 10% of them still have less than 10% of public housing units.

3.3 Neighborhood, public housing and unemployment: sample statistics

Table 2 provides a few sample statistics by neighborhood type and by whether the individual is tenant in the public sector or not. Deprived neighborhoods host almost one third of the individuals in our sample. Among deprived neighborhoods, 42% of individuals are tenants in the public sector, against only 9% in other neighborhoods. Other residents in deprived neighborhoods are either renters in the private sector or homeowners (35% and 58% of them respectively). Despite the spatial concentration of public housing, about one third of public housing renters in our sample are located in neighborhoods that are not classified as deprived. Thus, the diversity of situations regarding the combination of tenures and neighborhood types allows us to disentangle the effect of the two residential variables.

As implied by our classification, individuals in deprived neighborhoods are less educated and have lower occupational statuses. They are more often unemployed and a larger share of them is of foreign nationality. Among residents in deprived neighborhoods, these characteristics are more pronounced for public housing tenants. Yet, public housing tenants in not-deprived neighborhoods have more favorable characteristics than those in deprived locations: a smaller share is of foreign nationality, they are more educated and belong more often to the intermediate professional category. This accounts for the fact that public housing tenants have some latitude in choosing a location, at least if their economic situation allows it. On the other hand, whatever their location, public housing renters share similar demographic characteristics as to the number and age of children, due to the use of these criteria in the attribution of public housing units.

As expected, unemployment rate varies markedly with respect to the residential situation.[15] Whatever their location, public housing tenants are more often unemployed than others: one aim of the public housing sector is to provide individuals in a poor economic situation with affordable housing. Still, public housing occupants are by 55% more often unemployed if they are in a deprived neighborhood. Individuals with other housing tenures display a similar picture: their unemployment rate in deprived neighborhoods is by about 60% higher than in other neighborhoods. This differentiated unemployment rate depending on neighborhood type

[15] Remark that the overall unemployment rate is different from the rate displayed in Table A.2 due to the sample definition.

raises three interpretations. First, this can be the result of a sorting based on observables: due to the spatial variation in housing prices, unemployed individuals are less likely to be able to afford the best-located housing units. Second, it can be the consequence of a self-selection effect based on unobservables, such that people less likely to find a job sort themselves into deprived neighborhoods. Third, this could account for peer effects that increase individual difficulties on the labor market when they live in a deprived neighborhood. Our econometric analysis is intended to disentangle these different mechanisms.

4 Results

In this section, we present in turn results of simple probits, results of the simultaneous probit model, neighborhood and public housing predicted effects, followed by some discussion of exclusion restrictions and robustness checks.

4.1 Probit estimates

Table 3 contains marginal effects estimated from three simple probits: being a renter in the public sector, being located in a deprived neighborhood, and being unemployed, the latter being estimated in turn with and without the two residential variables. As expected, demographic variables take a large part in determining the probability of being accommodated in a public housing unit. Households with four children and more or with young children are more likely to rent a public housing unit, which is in line with assignment rules of public housing offices. Individuals (or their spouse) of foreign nationality or, to a lower extent, French people born abroad are more often housed in the public sector than French people. This observation might reflect the fact that foreign individuals are pushed toward the public housing sector due to discrimination on the housing market. As far as socioeconomic variables are concerned, occupational status along with education explain the propensity to live in a public housing unit. Blue-collar workers are more likely to rent a public housing unit than intermediate professions (the reference category) by 10 points, and office workers by 7 points. The lower the educational level is, the higher the probability of being tenant in the public housing sector. The spouse's educational level also determines public housing occupancy: the possibility to have or not a second wage in the household (low educated women having a weak incentive to take part in the labor-force) is naturally important in determining residential choices and is considered by public housing offices during the application process.

The second column of Table 3 gives marginal effects estimated from the neighborhood equation. A far as socioeconomic variables are concerned, marginal effects are similar to marginal effects in the public housing equation. As expected, nationality, education and professional status determine the probability to live in a deprived neighborhood, even after conditioning for accommodation in the public housing sector.[16] On the contrary, demographic variables do not explain the probability to live in a deprived neighborhood: neither the age of the household head, nor the number of children and the presence of young children that were introduced in a previous specification, had significant coefficients. This shows that the demographic situation of the household is among the criteria that are considered by public housing offices, whereas it is less relevant in determining residential location choice for other tenures. Finally, the public housing variable is the most powerful in explaining neighborhood choice and it has the strongest marginal effect. The introduction of this variable significantly improves the likelihood of the model.[17] Being a renter in the public sector increases by 33 points the probability to live in a deprived neighborhood, and as will be clear in next subsection from the simultaneous estimation of the three probits, this estimate does not suffer from any endogeneity bias.

The third and fourth columns of Table 3 give marginal effects for the unemployment equation with and without the two residential variables. We find very conventional results regarding individual determinants of employment status. Young individuals are more often unemployed, and the probability to be unemployed declines until the age of 43, after which it increases again, which is in line with observed unemployment rates by age. Individuals without any diploma or with only a short vocational training are more likely not to have a job, whereas people who were previously independent workers or executives are less unemployed than others. Marginal effects do not change much with the introduction of the two residential variables (column 4 compared to column 3). Probit estimates show that the unemployment probability increases both with location in a deprived neighborhood and with accommodation in the public sector, the latter being even more important than the former. However, these estimation results very likely suffer from an endogeneity bias.

4.2 Simultaneous probit model estimates

Table 4 presents the results of the simultaneous probit model. Coefficients of the public housing and neighborhood equations being very similar to the simple probit results, we do not comment

[16]Significance of estimated coefficients do not change with the introduction of the public housing variable, with the exception of age and intermediate profession dummies whose significance decreases.

[17]The statistic of the likelihood ratio test is 634.15 and the critical value for a $\chi^2_{0.01}(1)$ is 6.63.

on them here. For the same reasons, we do not comment on exogenous variables affecting unemployment propensity.

Remark first that the correction of the covariance matrix to account for potential correlations within each neighborhood slightly changes the coefficient standard errors, but does not change the significativity with respect to conventional thresholds.[18] This is not surprising, since neighborhoods which are classified as deprived are spread in different parts of the city. There is no reason why each of them would be concerned by a common shock.

The two correlation coefficients involving the public housing equation (ρ_{13} and ρ_{23}) are not significant, suggesting that the public housing variable is not endogenous in the unemployment equation, nor in the neighborhood equation. Note that we obtain this result of no correlation, although the employment status is not taken into account in the public housing equation, which might have resulted in a significant positive correlation as explained in section 2.2. This result conforts the validity of using a triangular system in which the effect of unemployment propensity is taken into account only through observable characteristics: if unobservables affecting unemployment probability were to influence public housing accommodation, a significant correlation between the error terms of the unemployment and public housing accommodation should be observed. Furthermore, the absence of correlation between the neighborhood type equation and the public housing equation shows that households are not deterred from applying to public housing accommodation by the spatial distribution of public housing units.[19] If this were not the case, unobservables affecting neighborhood choice would be correlated with those affecting public housing occupancy. This is coherent with the fact that the application process allows households to express spatial preferences, which permits those in search of better locations to rent nonetheless in the public housing sector.

The correlation coefficient between the error terms of the neighborhood and unemployment equations (ρ_{12}) is significantly different from zero at the 5% level, showing as expected that the neighborhood type is endogenous in the unemployment equation and that coefficients estimated from a simple probit are biased. This correlation is negative, suggesting that individuals having a higher propensity for unemployment than explained by their observed characteristics are less likely to live in a deprived neighborhood. This finding is counterintuitive and deserves some comments. First, the negative correlation could be interpreted as the consequence of the existence of mixed neighborhoods in Lyon's urban core. These neighborhoods are not classified

[18]Detailed results of uncorrected standard errors available from the authors upon request.

[19]This absence of correlation holds when we estimate a two probit system of neighborhood type and public housing occupancy, be unemployment introduced or not in the two residential equations.

as deprived but simultaneously have unemployment rates above the average. They host younger individuals, with potentially less predictable paths that could ensue in this negative correlation. Second, unemployment probability represents both the fact of having lost one's job and having not found a new one. The first component, which strongly depends on the firm's behavior, might be considered as more random from our point of view. The negative correlation might show that this component is higher in good neighborhoods, whereas unemployed individuals in deprived neighborhoods would have a more "structural" unemployment propensity. This interpretation means that the negative correlation would not be observed for the propensity of long-term unemployment, as the latter relates more to the individual's characteristics. Indeed, estimating our simultaneous probit model for long-term unemployment (replacing the probability of unemployment by the probability of having been unemployed for more than one year) shows no correlation between unemployment and neighborhood (see Table 5 column 3).[20] Finally, it is worth to note that some previous research on neighborhood effects also found results that run against the expected positive selection of workers with good unobservables into locations providing a better environment. Goux and Maurin (2007) in the French case find an upward bias of OLS estimate of neighborhood effects on schooling. Bolster et al. (2007) find higher levels of income growth in deprived areas, which is not what would be expected from the selection biases usually assumed. In the US, Bayer and Ross (2006) find IV estimates of neighborhood effects on labor-market outcomes higher than the OLS estimates. They interpret this result as the consequence of a sorting such that individuals with poor unobservables regarding the labor market compensate by location into neighborhoods that provide better prospects. Liebman et al. (2004) have non standard results regarding the selection of households into locations. Interestingly, they also find some support for interpreting this result as the consequence of differences in the observational period of time of experimental and non experimental samples.

Turning to estimated coefficients, the deprived neighborhood variable exerts a positive effect on unemployment probabilities. The effect of neighborhood type on unemployment can be computed as the difference in conditional probabilities, that themselves are calculated on the basis of joint probabilities. As suggested by Wooldridge (2001, p. 467), predicted effects are calculated for each individual and averaged over the sample. The effect of living in a deprived neighborhood on unemployment probability is :

$$\frac{1}{N}\sum_{i=1}^{N}\left[P(y_{i1}=1|y_{i2}=1)-P(y_{i1}=1|y_{i2}=0)\right] \tag{4.1}$$

with i indexing individuals, y_{i1} and y_{i2} designing unemployment and neighborhood type respec-

[20] Remark that the estimated effect of neighborhood on long-term unemployment is lower than that estimated for whole unemployment. This is not surprising as this effect applies to a lower baseline rate.

tively, and with conditional probabilities calculated as follows:

$$
\begin{aligned}
P(y_{i1}=1|y_{i2}=1) &= \frac{P(y_{i1}=1,y_{i2}=1)}{P(y_{i2}=1)} \\
&= \frac{P(y_{i1}=1,y_{i2}=1,y_{i3}=1)+P(y_{i1}=1,y_{i2}=1,y_{i3}=0)}{\left[\begin{array}{l} P(y_{i1}=1,y_{i2}=1,y_{i3}=1)+P(y_{i1}=1,y_{i2}=1,y_{i3}=0) \\ +P(y_{i1}=0,y_{i2}=1,y_{i3}=1)+P(y_{i1}=0,y_{i2}=1,y_{i3}=0) \end{array}\right]}
\end{aligned} \tag{4.2}
$$

and similarly for $P(y_{i1}=1|y_{i2}=0)$.

Table 5 shows the effects of neighborhood and public housing accommodation on unemployment following several specifications. As far as neighborhood effect is concerned, column 1 displays the "naive" effect of +1.48 probability points that is calculated on the basis of the simple probit. Consistently with the endogeneity of neighborhood type and the negative correlation, the effect estimated from the simultaneous probit model (column 2) is higher than in the probit model, with an increase in unemployment probability by 2.21 probability points.[21]

As to public housing accommodation, its coefficient in the three probit model is not significant. This result rules out any direct effect of public housing accommodation on unemployment. However, being housed in a public housing unit increases the probability to live in a deprived neighborhood, giving rise to an indirect effect that can be calculated as follows (with conditional probabilities calculated on the basis of joint probabilities as in equation 4.2):

$$
\frac{1}{N}\sum_{i=1}^{N}\left[P(y_{i1}=1|y_{i3}=1)-P(y_{i1}=1|y_{i3}=0)\right] \tag{4.3}
$$

The predicted effect of public housing occupancy on unemployment probability is +4.1 probability points in the baseline specification (Table 5, column 2). This effect is entirely due to the influence of public housing on neighborhood choice and its intensity is due to the large impact of public housing accommodation on the probability to live in a deprived neighborhood.

In summary, living in one of the 35% of Lyon's neighborhoods that have been identified as having the worst combination of social characteristics in our data analysis step increases the probability for household heads of being unemployed by slightly more than 2 probability points.

[21] While calculating the standard errors of these effects in the simultaneous probit case would be cumbersome, we calculated it for a two probit system in which we do not account for public housing occupancy and where spouse's educational level is used as exclusion. We used the delta method, that allows to approximate the variance of a vector-valued function of a random vector X. It is based on the following general result: $Var(G(X))=(\partial G/\partial \bar{X})'Var(X)(\partial G/\partial \bar{X})$ where $\bar{X}$ is the mean of X, $Var(X)$ is the variance-covariance matrix of X, $G()$ is a vector function and $G'()$ its matrix of first derivatives. Estimated neighborhood effect in this specification is +2.24 (Table 5, column 6) and the standard error shows that this effect is significant.

The change of neighborhood type amounts on average to an increase in neighbors' unemployment rate by 9.3%. By way of comparison, Topa (2001) found, in the case of Chicago in 1990, that an increase by 8% in the employment of neighboring tracts would increase employment rate by 1.3 %. As far as public housing is concerned, our results indicate that only an indirect effect exists, according to which being housed in the public sector increases unemployment probability by 4.1%.

4.3 Overidentification tests and discussion of specification

To be valid, our exclusion restrictions must verify two conditions: excluded variables have to be correlated with the endogenous residential variables which they are supposed to explain, while not being correlated with the error terms of the equations they are supposed to identify.

We first have to check the relevance of our exclusions, that is, the fact that spouse's educational level affects neighborhood type, and that the two variables describing household's children influence the probability of being accommodated in the public housing sector. To that aim, we performed likelihood ratio tests for the joint significance of the children variables in the public housing probit equation and of the dummies for spouse's educational level in the probit neighborhood equation. Those tests prove the relevance of these exclusions.[22]

The second condition amounts to the assumption that excluded variables have, after conditioning on other covariates, no correlation with the error terms of the unemployment equation. Considering first the unemployment equation, the question is to know whether having 4 children or more and having young children affects unemployment propensity. While this could be questionable if we were to work on a sample of women, whose behavior on the labor-market can be determined by the presence of children, this is less problematic given that our sample only involves males. The same question arises concerning the correlation between the spouse's educational level and the individual's unemployment probability. Such a correlation could be for instance the result of assortative mating, if one is to imagine that educated spouses married more able or motivated individuals. Furthermore, it is also necessary for the children-related variables not to influence neighborhood choices. In order to answer these questions, we performed a test for the validity of the chosen exclusions. Indeed, given that several dummies are used as exclusions, it is possible to perform standard overidentifying tests by considering

[22]The test statistic for the joint significance of "young children" and "4 children or more" in the public housing probit equals 61.01 and that for spouse's educational level in the neighborhood probit is 47.96. Both show statistical significance far beyond the standard 1% level.

the unemployment equation and the neighborhood equation as linear probability models. We performed a Hansen test for the validity of these instruments in the unemployment equation in which both neighborhood type and public housing occupancy are considered as endogenous. The same test was also used to test for the validity of the children-related variables as exclusions in the neighborhood equation. These tests do not allow to reject the assumption that our exclusions are valid.[23]

Furthermore, the three probits model was estimated with other exclusion restrictions, using the age of the spouse instead of the variables describing the children. Results are very similar to those of the baseline specification (Table 5, column 4). We also estimated a two probits model of unemployment and neighborhood type in which we use the spouse's educational level as exclusion and we do not account for the type of tenancy. We obtain results which are very similar to those of the baseline specification (Table 5, column 6).

Another potential problem affecting our identification strategy is the coherency condition that prevents the inclusion of the unemployment variable in the two residential equations. The question is to know whether not including unemployment in the two residential equations hinders the proper identification of the neighborhood effect and public housing effect. Of course, the most obvious influence of being unemployed that we can not account for is on assignment of a public housing unit.

Remark first that the absence of correlation between the error terms of the public housing equation and unemployment equation suggests that unobservables affecting both behaviors are not correlated. This finding is comforted by the estimation of a two probits model of unemployment and public housing in which unemployment is considered as a determinant of public housing accommodation (and no effect of public housing on unemployment is assumed so that the coherency condition is satisfied). In this case also, we do not observe any significant correlation between the two error terms.[24] Those results suggest that unemployment influences public housing only through observable characteristics, and not through unobservables. As to interpretation, those findings could be related to the fact that, although unemployed individuals may be more likely to obtain a public housing unit, we consider here the cross section of all

[23]We use the Hansen overidentification test because heteroscedasticity is likely to be present in a linear probability model. The test statistic for the validity of overidentifying restrictions in the unemployment equation is 5.574. It is distributed $\chi^2(4)$ under the null of valid instruments and its p-value is 0.233. The test statistic for the validity of exclusions in the neighborhood equation is 0.0049. It is distributed $\chi^2(1)$ under the null of valid instruments and its p-value is 0.825.

[24]Results available from the authors on request.

public housing renters, who are likely to have left unemployment but remained in the public housing sector in order to benefit from reduced housing rents.

Moreover, the two residential equations in our model are reduced-form equations, as described for instance in Blundell and Smith (1994). What is important in this case is to have exclusion restrictions and to properly predict the two residential variables. The estimation of probit equations for neighborhood type and public housing accommodation shows that predicted probabilities for the two variables do not change much, be employment status included or not in the covariates. Indeed, the percentage of correct predictions in the probit of neighborhood type hardly changes with the introduction of employment status in the covariates (from 76.17% to 76.20%). The same holds for the public housing equation (with predicted probabilities of 82.49% and 82.61% without and with unemployment respectively). Therefore, we can conclude that not including the employment status on the right hand side of the two residential equations does not hinder the identification of neighborhood effects.

We also performed a few robustness checks. Note first that the estimations were performed for different initial values of correlation coefficients and all of them converged to the same correlation matrix and produced very similar coefficients. Other specifications differing with respect to exogenous explanatory variables were also estimated without changing the baseline results. In particular, we estimated the model with a specification in which the individual's occupational status is assumed to be unobserved. This means that we drop the individual's occupational status in the three equations. By doing so, we neglect a characteristic which is quite important in determining the individual's behavior on the labor market and the housing market. As expected, the correlation of residuals and the predicted marginal effect of neighborhood increase (Table 5, column 5) compared with the baseline specification. However, the raise of the neighborhood effect remains limited. Although this is only an informal way of assessing the effect of unobserved heterogeneity, these additional results suggest that our estimation method allows to properly correct for unobserved heterogeneity affecting residential choice and labor-market toucomes.

Furthermore, we wanted to know whether our results are sensitive with respect to changes in the neighborhood classification. Therefore, we estimated the three probits model for two other classifications differing with respect to the variables included in the principal components analysis. These new classifications amounted to changing the classification of 188 and 303 individuals in each case. These new estimations gave very similar results compared to our baseline model, which confirms both our results and the choice of our classification method.

5 Conclusion

The objective of the present paper was to examine how unemployment probability is influenced both by accommodation in the public housing sector and neighborhood deprivation. Neighborhood types are defined through a data analysis step based on their social composition. Contrary to previous work, we do not consider the location of public housing renters as exogenous *ex ante*. Therefore, we estimate simultaneously three probit equations relating respectively to unemployment, neighborhood type, and accommodation in the public housing sector, thus allowing to deal with endogeneity of the two residential variables with respect to unemployment. Potential dependencies within neighborhoods are accounted for by the estimation of a robust variance matrix. Identification of this system takes advantage of the French process of public housing assignment, that allows the use of exclusion restrictions based on the demographic situation and spouse's characteristics. Estimation of this system is performed on a sample of more than 10,000 household heads by means of a simulated maximum likelihood method.

Our results do not provide any support to the hypothesis according to which public housing accommodation would affect job search behavior and, in particular, would reduce residential mobility sufficiently so as to increase unemployment probability. As to the influence of location, we clearly observe a neighborhood effect on unemployment. These findings both add to the literature on neighborhood effects and give insight into a much debated policy issue in France and in other countries, that is, the effect of the location of public housing on individual socioeconomic outcomes. Our results provide support to a recent French law aimed at lessening the spatial concentration of public housing units. Indeed, we show that location influences labor-market outcomes and that public housing occupancy strongly drives location choices. Our study also highlights that the particular situation of the public housing sector in France provides a valuable opportunity to estimate the impact of neighborhood on socioeconomic outcomes.

Besides empirical results, our paper highlights the importance of properly taking the endogeneity of residential location into account, when estimating its effects on unemployment. Indeed, it appears that estimating the effect of residing in a deprived neighborhood from a naive single probit equation underestimates this effect, compared to the effect obtained from the three probits system. As in several recent contributions in this field, we find non standard results concerning the direction of the bias of estimated effects if the endogeneity of neighborhood choice is not corrected for. This probably calls for future work in order to interpret this set of new results. Moreover, our methodology allows to distinguish between direct and indirect effects of public housing occupancy. Indeed, while a single probit equation of unemployment suggests that being a tenant in the public sector significantly increases the unemployment probability, it appears that this effect is only an indirect one, which results from the concentration of public housing units in deprived neighborhoods. Of course, due to the chosen framework, this study does not allow us to estimate separately endogenous and contextual effects. Therefore, we are not able to test for the existence of a social multiplier, nor for specific mechanisms such as the role of social networks, stigma, or role models, but we keep these issues for future work.

References

ARNOTT, R. and ROWSE, J. (1987) Peer group effects and the educational attainment, *Journal of Public Economics*, 32(3), pp. 287-305.

BAYER P. and ROSS, S. (2006) Identifying individual and group effects in the presence of sorting: a neighborhood effects application, *NBER Working Papers*, 12211.

BAYER P., ROSS, S. and TOPA, G., (2005) Place of work and place of residence: informal hiring networks and labor market outcomes, *NBER Working Papers*, 11019.

BENABOU, R. (1993) Workings of a city: location, education and production, *Quarterly Journal of Economics*, 108(3), pp. 619-652.

BLUNDELL, R. and SMITH R.J. (1994) Coherency and estimation in simultaneous models with censored or qualitative dependent variables, *Journal of Econometrics*, 64, pp. 355-373.

BOLDUC, D. (1999) A practical technique to estimate multinomial probit models in transportation, *Transportation Research Part B: Methodological*, 33(1), pp. 63-79.

BOLSTER, A., BURGESS, S., JOHNSTON, R., JONES, K., PROPPER, C. and SARKER, R. (2007) Neighbourhoods, households and income dynamics: a semi-parametric investigation of neighbourhood effects, *Journal of Economic Geography*, 7(1), pp. 1-36.

CAPPELARI, L. and JENKINS, S. (2003) Multivariate Probit Regression Using Simulated Maximum Likelihood, *The Stata Journal*, 3(3).

CRANE, J. (1991) The epidemic theory of ghettos and neighborhood effects on dropping out and teenage childbearing. *American Journal of Sociology*, 96(5), pp. 1226-1259.

DEBRAND, T. and TAFFIN, C. (2005) La mobilité résidentielle depuis 20 ans: des facteurs structurels aux effets de la conjoncture, *Economie et Statistique*, 381-382, pp. 125-145.

DUNCAN, O.D. and DUNCAN, B. (1955) A methodological analysis of segregation indexes, *American Sociological Review*, 41, pp. 210-217.

DURLAUF, S.N. and YOUNG, H.P. (2001) *Social dynamics*, Mit Press.

DURLAUF, S.N. (2004) Neighborhood effects, in HENDERSON, J.V. and THISSE, J.-F. (ed.) *Handbook of Regional and Urban Economics*, vol. 4, Elsevier, pp. 2173-2242.

FLATAU, P., FORBES, M., HENDERSHOTT, P.H. and WOOD, G. (2003) Homeownership and unemployment: the roles of leverage and public housing, *NBER Working Paper*, 10021.

GINTHER, D., HAVEMAN R. and WOLFE B. (2000) Neighborhood attributes as determinants of children's outcomes: how robust are the relationships? *Journal of Human Resources*, 35(4), pp. 603-642.

GLAESER, E.L., SACERDOTE, B. and SCHEINKMAN J.A. (1996) Crime and social interactions, *Quarterly Journal of Economics*, 111(2), pp. 507-548.

GLAESER, E.L. and SCHEINKMAN J.A. (2001) Measuring social interactions, in: DURLAUF, S.N. and YOUNG, H.P. (ed.) *Social Dynamics*, Mit Press, pp. 83-132.

GOBILLON, L., SELOD, H. and ZENOU, Y. (2007) The mechanisms of spatial mismatch, *Urban Studies*, forthcoming.

GOUX, D. and MAURIN, E. (2007) Close Neighbours Matter: Effects on Early Performance at School, *Economic Journal* (forthcoming).

GREENE, W.H. (1998) Gender Economics Courses in Liberal Arts Colleges: Further Results, *Journal of Economic Education*, 29(4), pp. 291-300.

HOLZER, H. (1988) Search method used by unemployed youth, *Journal of Labour Economics*, 6, pp. 1-20.

JACOB, B.A. (2004) Public housing, housing vouchers, and student achievement: Evidence from public housing demolitions in Chicago, *American Economic Review*, 94(1), pp. 233-258.

JACQUOT, A. (2007) L'occupation du parc HLM: un éclairage à partir des Enquêtes Logement, *Mimeo*, INSEE.

JOHNSTON, R.J., JONES, K., BURGESS, S., PROPPER, C., SARKER, R. and BOLSTER, A. (2004) Scale, factor analyses, and neighborhood effects, *Geographical Analysis*, 36(4), pp. 350-368.

KRAUTH, B. (2005) Peer effects and selection effects on smoking among Canadian youth, *Canadian Journal of Economics*, 38(3), pp. 735-757.

LIEBMAN, J.B., KATZ, L.F. and KLING, J.R. (2004) Beyond Treatment Effects: Estimating the Relationship Between Neighborhood Poverty and Individual Outcomes in the MTO Experiment. KSG Working Paper No. RWP04-036, Harvard University.

MADDALA, G.S. (1983) *Limited-dependent and Qualitative Variables in Econometrics*, Cambridge: Cambridge University Press.

MANSKI, C. (1993) Identification of endogenous social effects: the reflection problem, *Review of Economic Studies*, 60, pp. 531-542.

MOFFITT, R.A. (2001) Policy intervention, low-level equilibria, and social interactions, in: DURLAUF, S.N. and YOUNG, H.P. (ed.) *Social dynamics*, Mit Press., pp. 45-82.

O'REGAN, K.M. and QUIGLEY, J.M. (1998) Where youth live: economic effects of urban space on employment prospects, *Urban Studies*, 35(7), pp. 1187-1205.

OREOPOULOS, P. (2003) The long-run consequences of living in a poor neighborhood, *Quarterly Journal of Economics*, 118(4), pp. 1533-1575.

O.T.I.F. (2000) 10 ans de marché immobilier dans le Grand Lyon, *Observations immobilières*, Communauté Urbaine de Lyon.

RIVKIN, S. (2001) Tiebout sorting, aggregation and the estimation of peer group effects, *Economic of Education Review*, 20, pp. 201-209.

SELOD, H. and ZENOU, Y. (2001) Social interactions, ethnic minorities and urban unemployment, *Annales d'Economie et de Statistique*, 63-64, pp. 183-214.

TOPA, G. (2001) Social interactions, local spillovers and unemployment, *Review of Economic Studies*, 68, pp. 261-295.

WEINBERG, B., REAGAN, P.B. and YANKOW, J.J. (2004) Do neighborhoods affect work behavior? Evidence from the NLSY79. *Journal of Labor Economics*, 24, pp. 891-924.

WILDE, J. (2000) Identification of multiple equation probit models with endogenous dummy regressors, *Economic letters*, 69, pp. 309-312.

WILSON, W.J. (1987) *The Truly Disadvantaged*, Chicago, University of Chicago Press.

WOOLDRIDGE, J. (2001) *Econometric Analysis of Cross Section and Panel Data*, Cambridge: MIT Press.

WOOLDRIDGE, J. (2003) Cluster-sample methods in applied econometrics, *American Economic Review*, 93, pp. 133-138.

ZENOU, Y. and BOCCARD, N. (2000) Labor discrimination and redlining in cities, *Journal of*

Urban Economics, 48(2), pp. 260-285.

Appendix: Building of the neighborhood typology

	Factor 1	Factor 2
Eigenvalue	6.61	1.51
Percent of variance explained	73.47%	16.73%
Loadings		
% families with foreign household head	0.838	-0.152
% lone-parent households	0.619	0.535
% pop. with at most lower secondary education	0.958	-0.152
% pop. with high school final diploma	-0.908	0.402
% pop. with a university degree	-0.870	0.474
% executives	-0.867	0.420
% blue-collars	0.940	-0.169
% unemployed workers	0.837	0.494
% unemployed workers for more than one year	0.834	0.482

Only factors with eigenvalues superior or equal to 1 were retained.

Table A.1: List of variables used in the principal component analysis and their contributions to factors

	Deprived neighborhoods			Other neighborhoods			Total
	Mean	Min	Max	Mean	Min	Max	Mean
Public housing units (%)	43.8	0.0	98.5	9.1	0.0	50.2	21.3
Demography							
Foreign household heads (%)	19.9	0.0	56.9	6.1	0.0	15.8	10.9
Lone-parent families (%)	17.9	6.7	33.3	11.2	0.0	28.6	13.6
Education levels							
At most lower secondary edu. (%)	51.7	30.8	69.7	33.7	19.2	69.1	40.1
University degree (%)	13.3	4.0	43.3	30.7	7.2	54.3	24.6
Unemployment							
Unemployed workers (%)	18.3	9.2	37.3	9.0	4.0	20.4	12.3
Unemp. for more than 1 year (%)	9.9	4.3	22.0	4.3	1.3	9.4	6.3
Occupational status							
Blue-collars (%)	33.8	10.6	62.9	15.1	2.8	46.0	21.7
Executives (%)	7.5	0.0	29.7	22.3	4.0	47.6	17.1
Population	2,422	270	5,041	2,427	247	5,730	2,425
Total population		462,627			854,167		1,316,794
Number of neighborhoods		191			352		543

Table A.2: Mean characteristics of neighborhoods by type

	Employed individuals	Unemployed individuals	Total individuals
Number of observations	9,800	673	10,473
Residential characteristics			
Deprived neighborhood[(a)]	2,936 (29.96)	329 (48.89)	3,265 (31.17)
Tenure			
Renter in the public sector	1,751 (17.87)	256 (38.04)	2,007 (19.16)
Renter in the private sector	2,517 (25.68)	217 (32.24)	2,734 (26.11)
Homeowner	5,155 (52.60)	178 (26.45)	5,333 (50.92)
Other tenures	377 (3.85)	22 (3.27)	399 (3.81)
Personal characteristics			
Age	41.84	41.55	41.83
Nationality			
French born in France	8,003 (81.66)	423 (62.85)	8,426 (80.45)
French born abroad	966 (9.86)	86 (12.78)	1,052 (10.04)
Foreign nationality	831 (8.48)	164 (24.37)	995 (9.50)
Education level			
No diploma	1,256 (12.82)	167 (24.81)	1,423 (13.59)
At most lower secondary edu.	1,223 (12.48)	112 (16.64)	1,335 (12.75)
Vocational training	2,796 (28.53)	183 (27.19)	2,979 (28.44)
High school final diploma	1,261 (12.87)	71 (10.55)	1,332 (12.72)
University degree	3,264 (33.31)	140 (20.80)	3,404 (32.50)
Occupational status			
Farmer or independent worker	1,041 (10.62)	37 (5.50)	1,078 (10.29)
Executive	2,468 (25.18)	89 (13.22)	2,557 (24.42)
Intermediate professions (b)	3,204 (30.59)	154 (22.88)	2,685 (25.64)
Office worker	957 (9.77)	64 (9.51)	1,021 (9.75)
Blue-collar	2,803 (28.60)	329 (48.89)	3,132 (29.91)
Characteristics of the spouse			
Nationality			
French born in France	8,133 (82.99)	451 (67.01)	8,584 (81.96)
French born abroad	871 (8.89)	78 (11.59)	949 (9.06)
Foreign nationality	796 (8.12)	144 (21.40)	940 (8.98)
Education level			
No diploma	1,171 (11.95)	159 (23.63)	1,330 (12.70)
At most lower secondary edu.	1,517 (15.48)	125 (18.57)	1,642 (15.68)
Vocational training	2,185 (22.30)	143 (21.25)	2,328 (22.23)
High school final diploma	1,626 (16.59)	80 (11.89)	1,706 (16.29)
University degree	3,301 (33.68)	166 (24.67)	3,467 (33.10)
Number and age of children			
None	2,749 (28.05)	220 (32.69)	2,969 (28.35)
One	2,488 (25.39)	167 (24.81)	2,655 (25.35)
Two	2,905 (29.64)	144 (21.40)	3,049 (29.11)
Three	1,187 (12.11)	81 (12.04)	1,268 (12.11)
Four or more	471 (4.81)	61 (9.06)	532 (5.08)
Young children ($\leq$ 6 y.)	3,079 (31.42)	240 (35.66)	3,319 (31.69)

Figures give the mean value for continuous variables and frequency for discrete variables. Figures in brackets are % of the corresponding subsample.
(a) See definition in subsection 3.2. (b) Intermediate professions includes teachers and related, social and healthcare workers, clergy, civil service middle managers, sales and administrative middle managers, technicians, and supervisors.

Table 1: List of variables and summary statistics

	Deprived neigh.		Other neighborhoods		Total
	Public housing	Other tenures	Public housing	Other tenures	
Number of individuals	1,369	1,896	638	6,570	10,473
% of total sample	13.1	18.1	6.1	62.7	100.0
Unemployment rate	14.4	7.0	9.3	4.3	6.4
Tenure					
Homeowner	0.0	58.5	0.0	64.3	50.9
Renter in the private sector	0.0	35.2	0.0	31.5	26.1
Renter in the public sector	100.0	0.0	100.0	0.0	19.2
Other renter	0.0	6.2	0.0	4.3	3.8
Individual characteristics					
Age	39.9	42.0	39.2	42.4	41.8
Nationality					
French born in France	59.5	76.1	70.8	87.0	80.4
Fr. born abroad	14.7	11.3	12.2	8.5	10.0
Foreign nationality	25.9	12.6	16.9	4.5	9.5
Education					
No diploma	30.6	17.7	22.7	8.0	13.6
At most lower sec. edu.	16.2	15.5	15.2	11.0	12.7
Vocational training	33.9	31.8	35.9	25.6	28.4
High school final diploma	9.4	12.0	13.2	13.6	12.7
University degree	9.9	23.1	13.1	41.8	32.5
Occupational status					
Farmer or independent w.	2.8	10.7	4.6	12.3	10.3
Executive	3.9	15.6	7.2	32.9	24.4
Intermediate professions	14.8	26.8	22.4	27.9	25.6
Office worker	13.7	10.7	14.0	8.3	9.7
Blue-collar worker	64.9	36.2	51.9	18.7	29.9
Characteristics of the spouse					
Nationality					
French born in France	62.3	77.7	74.9	88.0	81.9
Fr. born abroad	13.3	10.7	9.6	7.7	9.1
Foreign nationality	24.4	11.6	15.5	4.4	9.0
Education					
No diploma	32.1	16.5	22.9	6.6	12.7
At most lower sec. edu.	18.8	17.4	19.4	14.2	15.7
Vocational training	27.6	25.2	27.7	19.7	22.2
High school final diploma	10.9	14.6	14.6	18.1	16.3
University degree	10.6	26.3	15.4	41.5	33.1
Number and age of children					
None	22.2	29.8	23.8	29.7	28.3
One	24.1	25.7	22.1	25.8	25.3
Two	26.7	27.5	29.0	30.1	29.1
Three	14.6	11.4	15.5	11.4	12.1
Four of more	12.3	5.6	9.6	3.0	5.1
Young children ($\leq$ 6 y.)	45.7	29.5	41.9	28.4	31.7

Figures give the mean value for continuous variables and frequency (%) for discrete variables.

Table 2: Sample characteristics by residential situation

Dependent variable	**Public housing**		**Deprived neighborhood**		**Unemployment Model 1**		**Unemployment Model 2**	
Residential variables								
Deprived neigh.							0.0148^{***}	(0.0052)
Public housing			0.3344^{***}	(0.0259)			0.0310^{***}	(0.0072)
Personal characteristics								
Age	-0.0082^{***}	(0.0032)	-0.0076^{NS}	(0.0047)	-0.0081^{***}	(0.0019)	-0.0079^{***}	(0.0018)
Squared age	$4*10\text{-}5^{NS}$	(4*10-5)	$7*10\text{-}5^{NS}$	(5*10-5)	$9*10\text{-}5^{***}$	(2*10-5)	$9*10\text{-}5^{***}$	(2*10-5)
Nationality								
French nationality	Ref.		Ref.		Ref.		Ref.	
Fr. born abroad	0.0606^{***}	(0.0143)	0.0481^{***}	(0.0171)	0.0226^{***}	(0.0092)	0.0185^{***}	(0.0087)
Foreign nation.	0.0939^{***}	(0.0200)	0.0881^{***}	(0.0231)	0.0610^{***}	(0.0135)	0.0508^{***}	(0.0128)
Education								
No diploma	0.0302^{**}	(0.0155)	0.0668^{***}	(0.0207)	0.0249^{**}	(0.0110)	0.0199^{*}	(0.0114)
$\leq$ lower sec. edu.	0.0248^{*}	(0.0153)	0.0564^{***}	(0.0204)	0.0228^{**}	(0.0110)	0.0203^{**}	(0.0112)
Vocational training	0.0112^{NS}	(0.0123)	0.0282^{NS}	(0.0181)	0.0036^{NS}	(0.0082)	0.0027^{NS}	(0.0086)
High school final dip.	Ref.		Ref.		Ref.		Ref.	
University degree	-0.0207^{*}	(0.0118)	-0.0161^{NS}	(0.0190)	-0.00095^{NS}	(0.0083)	0.0011^{NS}	(0.0089)
Occupational status								
Independent w.	-0.0943^{***}	(0.0099)	-0.0484^{***}	(0.0167)	-0.0297^{***}	(0.0062)	-0.0270^{***}	(0.0064)
Executive	-0.0859^{***}	(0.0105)	-0.0888^{***}	(0.0145)	-0.0197^{***}	(0.0064)	-0.0168^{**}	(0.0067)
Intermediate prof.	Ref.		Ref.		Ref.		Ref.	
Office worker	0.0736^{***}	(0.0164)	0.0299^{*}	(0.0184)	-0.0062^{NS}	(0.0080)	-0.0099^{NS}	(0.0076)
Blue-collar worker	0.1053^{***}	(0.0131)	0.0649^{***}	(0.0145)	0.0139^{**}	(0.0071)	0.0060^{NS}	(0.0071)
Characteristics of the spouse								
Nationality								
French nationality	Ref.		Ref.		Ref.		Ref.	
Fr. born abroad	0.0624^{***}	(0.0165)	0.0786^{***}	(0.0199)	0.0190^{**}	(0.0093)	0.0138^{*}	(0.0087)
Foreign nation.	0.0564^{***}	(0.0183)	0.0747^{***}	(0.0253)	0.0233^{**}	(0.0108)	0.0175^{*}	(0.0110)
Education								
No diploma	0.1438^{***}	(0.0201)	0.1141^{***}	(0.0205)				
$\leq$ lower sec. edu.	0.0884^{***}	(0.0169)	0.0493^{***}	(0.0175)				
Vocational training	0.0655^{***}	(0.0141)	0.0612^{***}	(0.0159)				
High school final dip.	Ref.		Ref.					
University degree	-0.0452^{***}	(0.0121)	-0.0054^{NS}	(0.0161)				
Number and age of children								
Four of more children	0.0776^{***}	(0.0202)						
Young children ($\leq$ 6 y.)	0.0484^{***}	(0.0096)						
Log likelihood	-4,038		-5,439		-2,359		-2,337	
Pseudo-R2	0.211		0.163		0.056		0.064	
# Observations	10.473		10.473		10.473		10.473	

Notes: ***, ** and * denote significance at the 1%, 5% and 10% level respectively. Each equation also includes a constant. Marginal effect are (a) for the age variables: $\beta\Phi(\beta\text{X})$ with $\Phi()$ the normal cumulative distribution function and β the vector of estimated coefficients and (b) for each dummy explanatory variable X_k: $\Phi(\beta X_{-k} + \beta_k) - \Phi(\beta X_{-k})$ with X_{-k} the vector of explanatory variables except X_k. X is taken at the sample mean.
Figures in brackets give standard errors of the marginal effects calculated by the delta method.

Table 3: Marginal effects from the three simple probits

	Public housing		Deprived neighborhood		Unemploy-ment	
Intercept	0.197^{NS}	(0.297)	-0.353^{NS}	(0.274)	-0.396^{NS}	(0.333)
Residential characteristics						
Public housing	-	-	0.775^{***}	(0.256)	-0.248^{NS}	(0.249)
Deprived neighborhood	-	-	-	-	0.755^{***}	(0.279)
Personal characteristics						
Age	-0.038^{***}	(0.015)	-0.023^{NS}	(0.014)	-0.067^{***}	(0.016)
Squared-age	0.00020^{NS}	(0.0002)	0.00021^{NS}	(0.0002)	0.0008^{***}	(0.0002)
Nationality						
French born in France	Ref.		Ref.		Ref.	
French born abroad	0.249^{***}	(0.054)	0.149^{***}	(0.050)	0.144^{**}	(0.066)
Foreign nationality	0.367^{***}	(0.069)	0.267^{***}	(0.067)	0.333^{***}	(0.081)
Level of education						
No diploma	0.129^{**}	(0.064)	0.194^{***}	(0.057)	0.128^{NS}	(0.089)
At most lower sec. edu.	0.108^{*}	(0.064)	0.161^{***}	(0.056)	0.139^{*}	(0.083)
Vocational training	0.048^{NS}	(0.055)	0.082^{NS}	(0.051)	0.012^{NS}	0.075)
High school final diploma	Ref.		Ref.		Ref.	
University diploma	-0.101^{*}	(0.056)	-0.048^{NS}	(0.056)	0.006^{NS}	(0.080)
Occupational status						
Farmer or independent worker	-0.563^{***}	(0.074)	-0.155^{***}	(0.059)	-0.291^{***}	(0.085)
Executive	-0.449^{***}	(0.061)	-0.275^{***}	(0.046)	-0.140^{**}	(0.070)
Intermediate professions	Ref.		Ref.		Ref.	
Office worker	0.298^{***}	(0.058)	0.097^{*}	(0.055)	-0.081^{NS}	(0.080)
Blue-collar	0.440^{***}	(0.047)	0.204^{***}	(0.051)	0.055^{NS}	(0.069)
Characteristics of the spouse						
Nationality						
French born in France	Ref.		Ref.		Ref.	
French born abroad	0.257^{***}	(0.061)	0.227^{***}	(0.055)	0.089^{NS}	(0.070)
Foreign nationality	0.236^{***}	(0.069)	0.216^{***}	(0.071)	0.120^{NS}	(0.090)
Level of education						
No diploma	0.537^{***}	(0.064)	0.343^{***}	(0.066)	-	-
At most lower sec. edu.	0.351^{***}	(0.062)	0.161^{***}	(0.054)	-	-
Vocational training	0.275^{***}	(0.055)	0.186^{***}	(0.046)	-	-
High school final diploma	Ref.		Ref.		-	-
University diploma	-0.222^{***}	(0.060)	-0.013^{NS}	(0.049)	-	-
Number and age of children						
Four or more children	0.306^{***}	(0.073)	-	-	-	-
Young children ($\leq$ 6 y.)	0.208^{***}	(0.040)	-	-	-	-
Correlation of residuals unemp./deprived neigh. ρ_{12}			-0.355^{**}(0.150)			
Correlation of residuals unemp./public housing ρ_{13}			0.166^{NS}(0.118)			
Correlation of residuals deprived neigh./pub. housing ρ_{23}			0.071^{NS}(0.138)			
Log likelihood			-11,812			
LR test ($\rho_{12} = \rho_{23} = \rho_{23} = 0$)			3.5408			
Pseudo-R^2			0.163			
Number of observations			10,473			

Notes: ***, ** and * denote significance at the 1%, 5% and 10% level respectively.
Estimation by simulated maximum likelihood with 600 draws.
Figures in brackets give robust standard errors corrected for dependencies within neighborhood.

Table 4: Estimated coefficients of the three probits system

	Single probit	Three probit model				Two probit model
		Baseline		Spouse's age in public housing eq.	Professional status omitted	Exclusion: spouse's educ.
		Unemployment	Long-term unemployment			
	(1)	(2)	(3)	(4)	(5)	(6)
Deprived neighborhood						
Coefficient	0.129^{***}	0.755^{***}	0.636^{**}	0.755^{**}	0.796^{***}	0.644^{**}
Correlation	-	-0.355^{**}	-0.250^{NS}	-0.348^{**}	-0.376^{***}	-0.274^{NS}
Marginal effect	0.0148	0.0220	0.0175	0.0219	0.0256	.0224
Public housing						
Marginal effect	0.0310	0.0410	0.0255	0.0405	0.0455	-
Log likelihood	-2,337	-11,812	-10,836	-11,828	-12,050	-
Pseudo-R2	0.064	0.163	0.172	0.161	0.146	-

Table 5: Effect of public housing and neighborhood on unemployment probability

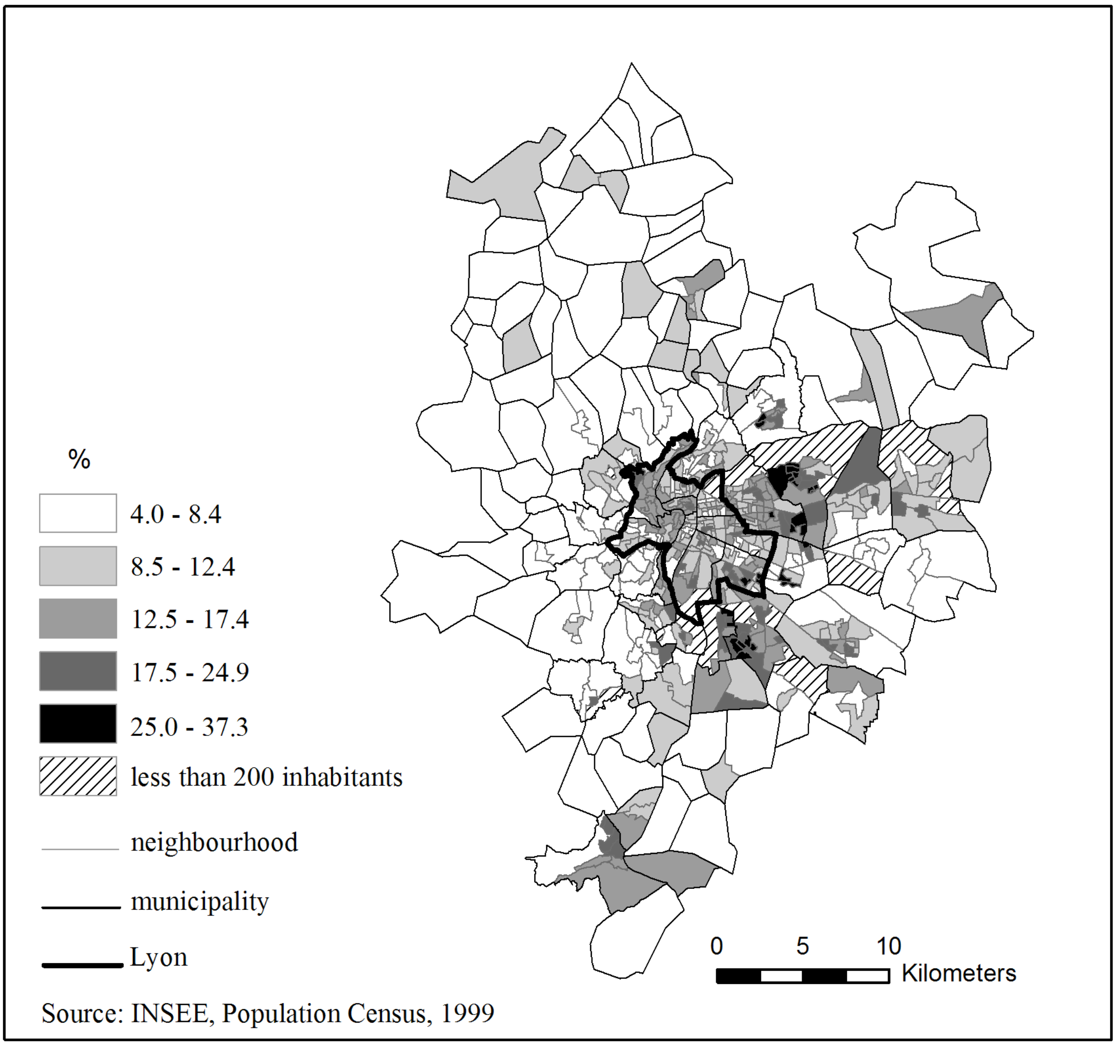

Figure 1: Percentage of unemployed workers within labor-force participants

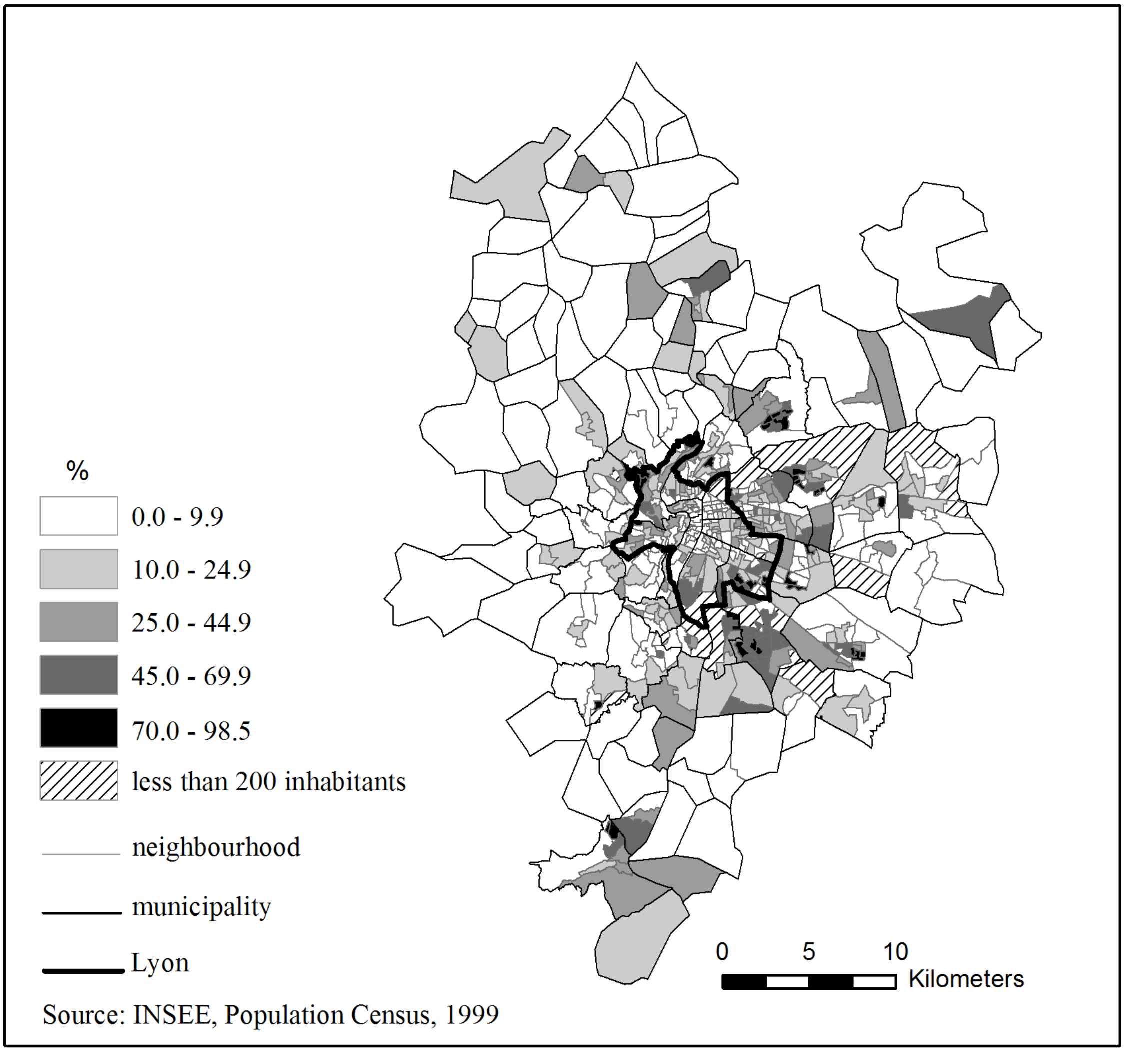

Figure 2: Percentage of housing units belonging to the public sector

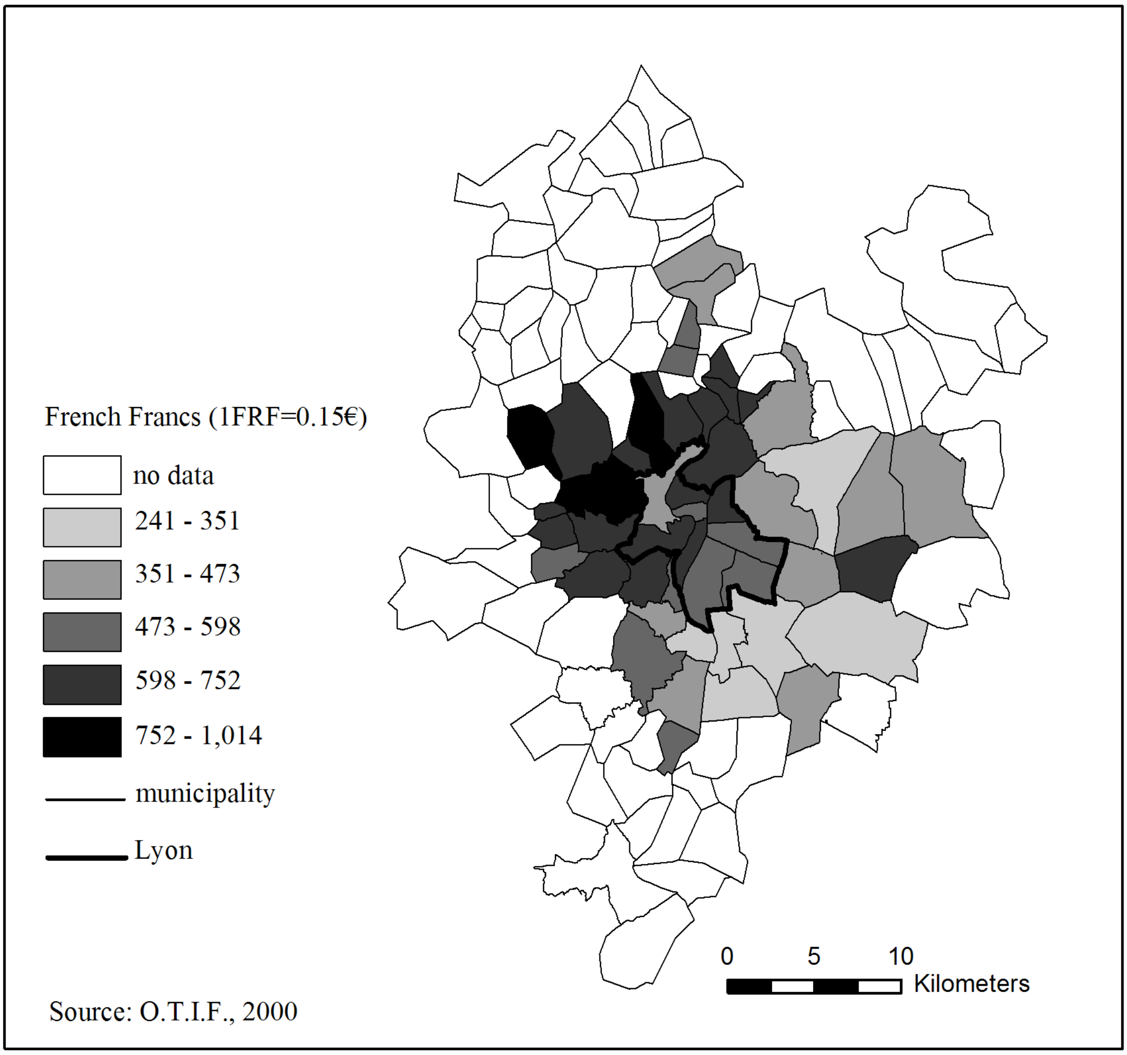

Figure 3: Mean housing prices by municipality

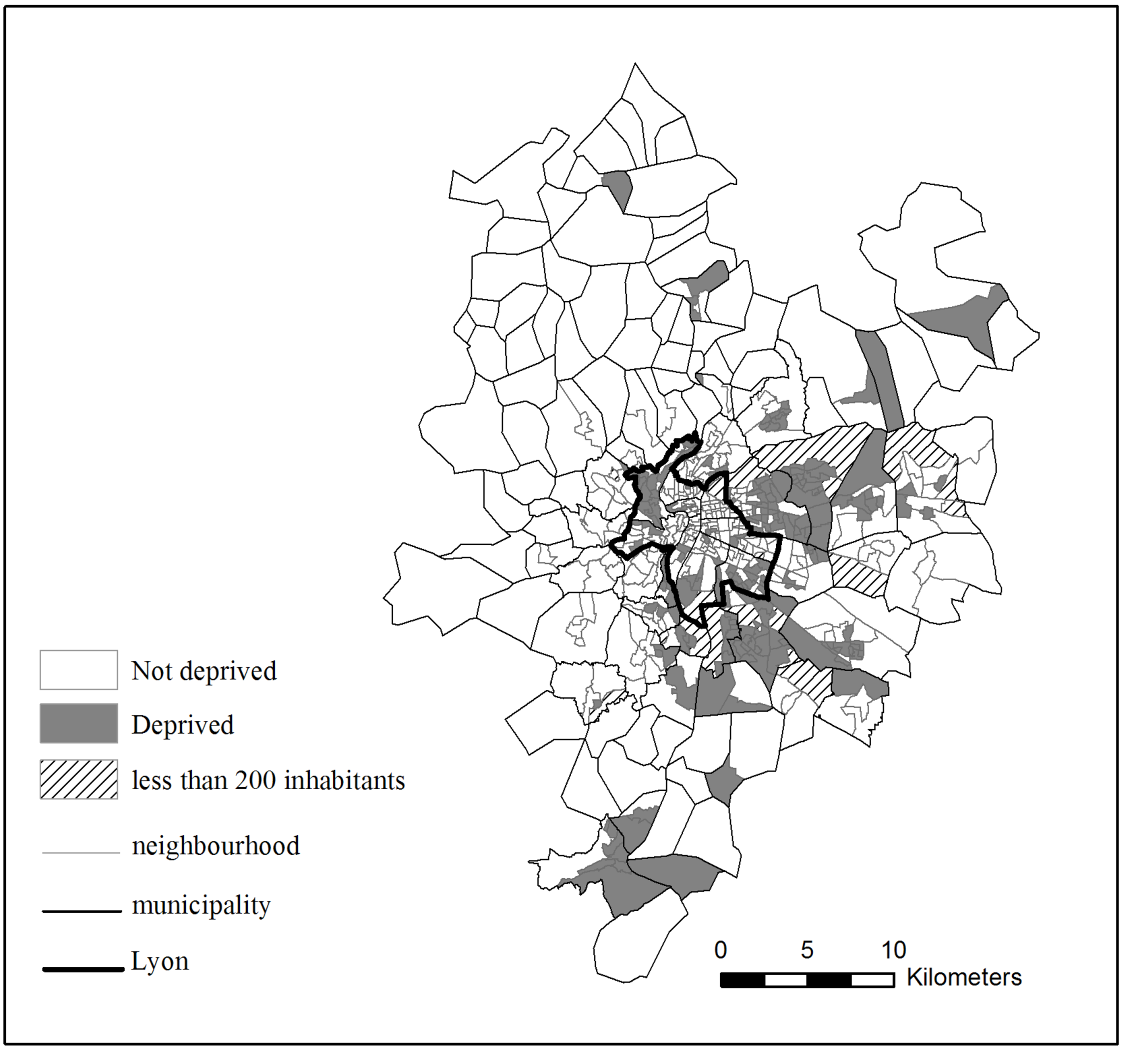

Figure 4: Location of deprived neighborhoods